MasakhaPOS: Part-of-Speech Tagging for Typologically Diverse African Languages

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Abstract

In this paper, we present MasakhaPOS, the largest part-of-speech (POS) dataset for 20 typologically diverse African languages. We discuss the challenges in annotating POS for these languages using the UD (universal dependencies) guidelines. We conducted extensive POS baseline experiments using conditional random field and several multilingual pretrained language models. We applied various cross-lingual transfer models trained with data available in UD. Evaluating on the Masakha-POS dataset, we show that choosing the best transfer language(s) in both single-source and multi-source setups greatly improves the POS tagging performance of the target languages, in particular when combined with cross-lingual parameter-efficient fine-tuning methods. Crucially, transferring knowledge from a language that matches the language family and morphosyntactic properties seems more effective for POS tagging in unseen languages.

1 Introduction

Part-of-Speech (POS) tagging is a process of assigning the most probable grammatical category (or tag) to each word (or token) in a given sentence of a particular natural language. POS tagging is one of the fundamental steps for many natural language processing (NLP) applications, including machine translation, parsing, text chunking, spell and grammar checking. While great strides have been made for (major) Indo-European languages such as English, French and German, work on the African languages is quite scarce. The vast majority of African languages lack annotated datasets for training and evaluating basic NLP systems.

There have been recent works on the development of benchmark datasets for training and evaluating models in African languages for various NLP tasks, including machine translation (NLLB-Team et al., 2022; Adelani et al., 2022a), text-tospeech (Ogayo et al., 2022; Meyer et al., 2022), speech recognition (Ritchie et al., 2022), sentiment analysis (Muhammad et al., 2022, 2023), news topic classification (Adelani et al., 2021, 2022b). However, there is no large-scale dataset for POS covering several African languages.

To tackle the data bottleneck issue for lowresource languages, recent work applied crosslingual transfer (Artetxe et al., 2020; Pfeiffer et al.,

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2020; Ponti et al., 2020) using multilingual pretrained language models (PLMs) (Conneau et al., 2020) to model specific phenomena in low-resource target languages. While such a cross-lingual transfer is often evaluated by fine-tuning multilingual models on English data, more recent work has shown that English is not often the best transfer language (Lin et al., 2019; de Vries et al., 2022; Adelani et al., 2022b).

Contributions In this paper, we develop MasakhaPOS — the largest POS dataset for 20 typologically diverse African languages. We highlight the challenges of annotating POS for these diverse languages using the universal dependencies (UD) (Nivre et al., 2016) guidelines such as tokenization issues, and POS tags ambiguities. We provide extensive POS baselines using conditional random field (CRF) and several multilingual pretrained language models (PLMs). Furthermore, we experimented with different parameter-efficient cross-lingual transfer methods (Pfeiffer et al., 2021; Ansell et al., 2022), and transfer languages with available training data in the UD. Our evaluation demonstrates that choosing the best transfer language(s) in both single-source and multi-source setups leads to large improvements in POS tagging performance, especially when combined with parameter-fine-tuning methods. Finally, we show that a transfer language that belongs to the same language family and shares similar morphological characteristics (e.g. Non-Bantu Niger-Congo) seems to be more effective for tagging POS in unseen languages. For reproducibility, we release our code, data and models on GitHub¹

2 Related Work

In the past, efforts have been made to build a POS tagger for several African languages, including Hausa (Tukur et al., 2020), Igbo (Onyenwe et al., 2014), Kinyarwanda (Cardenas et al., 2019), Luo (De Pauw et al., 2010), Setswana (Malema et al., 2017, 2020), isiXhosa (Delman, 2016), Wolof (Dione et al., 2010), Yorùbá (Sèmiyou et al., 2012; Ishola and Zeman, 2020), and isiZulu (Koleva, 2013). While POS tagging has been investigated for the aforementioned languages, annotated datasets exist only in a few African languages. In the Universal dependencies dataset (Nivre et al., 2016), nine African languages² are represented. Still, only four of the nine languages have training data, i.e. Afrikaans, Coptic, Nigerian-Pidgin, and Wolof. In this work, we create the largest POS dataset for 20 African languages following the UD annotation guidelines.

3 Languages and their characteristics

We focus on 20 Sub-Saharan African languages, spoken in circa 27 countries in the Western, Eastern, Central and Southern regions of Africa. An overview of the focus languages is provided in Table 1. The selected languages represent four language families: Niger-Congo (17), Afro-Asiatic (Hausa), Nilo-Saharan (Luo), and English Creole (Naija). Among the Niger-Congo languages, eight belong to the Bantu languages.

The writing system of our focus languages is mostly based on Latin script (sometimes with additional letters and diacritics). Besides Naija, Kiswahili, and Wolof, the remaining languages are all tonal. As far as morphosyntax is concerned, noun classification is a prominent grammatical feature for an important part of our focus languages. 12 of the languages actively make use of between 6-20 noun classes. This includes all Bantu languages, Ghomálá', Mossi, Akan and Wolof (Nurse and Philippson, 2006; Payne et al., 2017; Bodomo and Marfo, 2002; Babou and Loporcaro, 2016). Noun classes can play a central role in POS annotation. For instance, in isiXhosa, adding the class prefix can change the grammatical category of the word (Delman, 2016). All languages use the SVO word order, while Bambara additionally uses the SOV word order. Appendix A provides the details about the language characteristics.

4 Data and Annotation for MasakhaPOS

4.1 Data collection

Table 1 provides the data source used for POS annotation — collected from online newspapers. The choice of the news domain is threefold. First, it is the second most available resource after the religious domain for most African languages. Second, it covers a diverse range of topics. Third, the news domain is one of the dominant domains in the UD. We collected **monolingual news corpus** with an open license for about eight African languages, mostly from local newspapers. For the remaining

https://github.com/masakhane-io/
masakhane-pos

²including Amharic, Bambara, Beja, Yorùbá, and Zaar with no training data in UD.

Language	Family	African Region	No. of Speakers	Source	Train / dev / test	# Tokens	Average sentence Length (# Tokens)
Bambara (bam)	NC / Mande	West	14M	MAFAND-MT (Adelani et al., 2022a)	793/ 158/ 634	40,137	25.9
Ghomálá'(bbj)	NC / Grassfields	Central	1M	MAFAND-MT	750/ 149/ 599	23,111	15.4
Éwé (ewe)	NC / Kwa	West	7M	MAFAND-MT	728/ 145/ 582	28,159	19.4
Fon(fon)	NC / Volta-Niger	West	2M	MAFAND-MT	798/ 159/ 637	49,460	30.6
Hausa (hau)	Afro-Asiatic / Chadic	West	63M	Kano Focus and Freedom Radio	753/150/601	41,346	27.5
Igbo(ibo)	NC / Volta-Niger	West	27M	IgboRadio and Ka OdI Taa	803/ 160/ 642	52,195	32.5
Kinyarwanda (kin)	NC / Bantu	East	10M	IGIHE, Rwanda	757/151/604	40,558	26.8
Luganda (lug)	NC / Bantu	East	7M	MAFAND-MT	733/ 146/ 586	24,658	16.8
Luo(luo)	Nilo-Saharan	East	4M	MAFAND-MT	757/151/604	45,734	30.2
Mossi (mos)	NC / Gur	West	8M	MAFAND-MT	757/151/604	33,791	22.3
Chichewa (nya)	NC / Bantu	South-East	14M	Nation Online Malawi	728/ 145/ 582	24,163	16.6
Naija (pcm)	English-Creole	West	75M	MAFAND-MT	752/150/600	38,570	25.7
chiShona(sna)	NC / Bantu	South	12M	VOA Shona	747/ 149/ 596	39,785	26.7
Kiswahili (swa)	NC / Bantu	East & Central	98M	VOA Swahili	675/ 134/ 539	40,789	29.5
Setswana (tsn)	NC / Bantu	South	14M	MAFAND-MT	753/ 150/ 602	41,811	27.9
Akan/Twi(twi)	NC / Kwa	West	9M	MAFAND-MT	775/ 154/ 618	41,203	26.2
Wolof (wol)	NC / Senegambia	West	5M	MAFAND-MT	770/ 154/ 616	44,002	28.2
isiXhosa (xho)	NC / Bantu	South	9M	Isolezwe Newspaper	752/150/601	25,313	16.8
Yorùbá (yor)	NC / Volta-Niger	West	42M	Voice of Nigeria and Asejere	875/ 174/ 698	43,601	24.4
isiZulu(zul)	NC / Bantu	South	27M	Isolezwe Newspaper	753/ 150/ 601	24,028	16.0

Table 1: Languages and Data Splits for MasakhaPOS Corpus. Language, family (NC: Niger-Congo), number of speakers, news source, and data split in number of sentences.

12 languages, we make use of MAFAND-MT (Adelani et al., 2022a) **translation corpus** that is based on the news domain. While there are a few issues with translation corpus such as translationese effect, we did not observe serious issues in annotation. The only issue we experienced was a few misspellings of words, which led to annotators labeling a few words with the "X" tag. However, as a post-processing step, we corrected the misspellings and assigned the correct POS tags.

4.2 POS Annotation Methodology

For the POS annotation task, we collected **1,500** sentences per language. As manual POS annotation is very tedious, we agreed to manually annotate 100 sentences per language in the first instance. This data is then used as training data for automatic POS tagging (i.e., fine-tuning RemBERT (Chung et al., 2021) PLM) of the remaining unannotated sentences. Annotators proceeded to fix the mistakes of the predictions (i.e. 1,400 sentences). This drastically reduced the manual annotation efforts since a few tags are predicted with almost 100% accuracy like punctuation marks, numbers and symbols. Proper nouns were also predicted with high accuracy due to the casing feature.

To support work on manual corrections of annotations, most of the languages used the IO Annotator³ tool, a collaborative annotation platform for text and images. The tool provides support for multi-user annotations simultaneously on datasets. For each language, we hired three native speakers with linguistics backgrounds to perform POS annotation.⁴ To ensure high-quality annotation, we recruited a language coordinator to supervise annotation in each language. In addition, we provided online support (documentation and video tutorials) to train annotators on POS annotation. We made use of the Universal POS tagset (Petrov et al., 2012), which contains 17 tags.⁵ To avoid the use of spurious tags, for each word to be annotated, annotators have to choose one of the possible tags made available on the IO Annotator tool through a dropdown menu. For each language, annotation was done independently by each annotator. At the end of annotation, language coordinators worked with their team to resolve disagreements using IOAnnotator or Google Spreadsheet. We refer to our newly annotated POS dataset as MasakhaPOS.

4.3 Quality Control

Computation of automatic inter-agreement metrics scores like Fleiss Kappa was a bit challenging due to tokenization issues, e.g. many compound family names are split. Instead, we adopted the tokenization defined by annotators since they are annotating all words in the sentence. Due to several annotation challenges as described in section 5, seven language teams (Ghomálá', Fon, Igbo, Chichewa chiShona, Kiswahili, and Wolof) decided to engage annotators on online calls (or in person discussions) to agree on the correct annotation for each word in the sentence. The other language teams allowed their annotators to work individually, and only discuss sentences on which they did not agree. Seven of the 13 languages achieved a

³https://ioannotator.com/

⁴Each annotator was paid \$750 for 1,500 sentences. ⁵https://universaldependencies.org/u/pos/

sentence-level annotation agreement of over 75%. Two more languages (Luganda and isiZulu) have sentence-level agreement scores of between 64.0% to 67.0%. The remaining four languages (Ewe, Luo, Mossi, and Setswana) only agreed on less than 50% of the annotated sentences. This confirms the difficulty of the annotation task for many language teams. Despite this challenge, we ensured that all teams resolved all disagreements to produce high-quality POS corpus. Appendix B provides details of the number of agreed annotation by each language team.

After quality control, we divided the annotated sentences into training, development and test splits consisting of 50%, 10%, 40% of the data respectively. We chose a larger test set proportion that is similar to the size of test sets in the UD, usually larger than 500 sentences. Table 1 provides the details of the data split. We split very long sentences into two to fit the maximum sequence length of 200 for PLM fine-tuning. We further performed manual checks to correct sentences split at arbitrary parts.

5 Annotation challenges

When annotating our focus languages, we faced two main challenges: tokenization and POS ambiguities.

5.1 Tokenization and word segmentation

In UD, the basic annotation units are syntactic words (rather than phonological or orthographical words) (Nivre et al., 2016). Accordingly, clitics need to be split off and contraction must be undone where necessary. Applying the UD annotation scheme to our focus languages was not straightforward due to the nature of those languages, especially with respect to the notion of word, the use of clitics and multiword units.

5.1.1 Definition of word

For many of our focus languages (e.g. Chichewa, Luo, chiShona, Wolof and isiXhosa), it was difficult to establish a dividing line between a word and a phrase. For instance, the chiShona word *ndakazomuona* translates into English as a whole sentence ('I eventually saw him'). This word consists of several morphemes that convey distinct morphosyntactic information (Chabata, 2000): *Nda*- (subject concord), *-ka*- (aspect), *-zo*- (auxiliary), *-mu*- (object concord), *-ona*- (verb stem). This illustrates pronoun incorporation (Bresnan and

Mchombo, 1987), i.e. subject and/or object pronouns appear as bits of morphology on a verb or other head, functioning as agreement markers. Naturally, one may want to split this word into several tokens reflecting the different grammatical functions. For UD, however, morphological features such as agreement are encoded as properties of words and there is no attempt at segmenting words into morphemes, implying that items like *ndakazomuona* should be treated as a single unit.

5.1.2 Clitics

In languages like Hausa, Igbo, IsiZulu, Kinyarwanda, Wolof and Yorùbá, we observed an extensive use of cliticization. Function words such as prepositions, conjunctions, auxiliaries and determiners can attach to other function or content words. For example, the Igbo contracted form yana consists of a pronoun (PRON) ya and a coordinating conjunction (CCONJ) na. Following UD, we segmented such contracted forms, as they correspond to multiple (syntactic) words. However, there were many cases of fusion where a word has morphemes that are not necessarily easily segmentable. For instance, the chiShona word vave translates into English as 'who (PRON) are (AUX) now (ADV)'. Here, the morpheme -ve, which functions both as auxiliary and adverb, cannot be further segmented, even though it corresponds to multiple syntactic words. Ultimately, we treated the word vave as a unit, which received the AUX POS tag.

In addition, there were word contractions with phonological changes, posing serious challenges, as proper segmentation may require to recover the underlying form first. For instance, the Wolof contracted form "cib" (Dione, 2019) consists of the preposition ci 'in' and the indefinite article ab 'a'. However, as a result of phonological change, the initial vowel of the article is deleted. Accordingly, to properly segment the contracted form, it won't be sufficient to just extract the preposition ci because the remaining form b will not have meaning. Also, some word contractions are ambiguous. For instance, in Wolof, a form like *geek* can be split into *gi* 'the' and *ak* where *ak* can function as a conjunction 'and' or as a preposition 'with'.

5.1.3 One unit or multitoken words?

Unlike the issue just described in 5.1.2, it was sometimes necessary to go in the other direction, and combine several orthographic tokens into a single syntactic word. Examples of such multitoken words are found e.g. in Setswana (Malema et al., 2017). For instance, in the relative structure *ngwana yo o ratang* (the child who likes ...), the relative marker *yo o* is a multitoken word that matches the noun class (class 1) of the relativized noun *ngwana* ('child'), which is subject of the verb *ratang* ('to like'). In UD, multitoken words are allowed for a restricted class of phenomena, such as numerical expressions like 20 000 and abbreviations (e. g.). We advocate that this restricted class be expanded to phenomena like Setswana relative markers.

5.2 POS ambiguities

There were cases where a word form lies on the boundary between two (or more) POS categories.

5.2.1 Verb or conjunction?

In quite a few of our focus languages (e.g. Yorùbá and Wolof), a form of the verb 'say' is also used as a subordinate conjunction (to mark out clause boundaries) with verbs of speaking. For example, in the Yorùbá sentence Olú gbàgbé pé Bolá tí jàde (lit. 'Olu forgot that Bola has gone') (Lawal, 1991), the item *pé* seems to behave both like a verb and a subordinate conjunction. On the one hand, because of the presence of another verb gbàgbé 'to forget', the pattern may be analyzed as a serial verb construction (SVC) (Oyelaran, 1982; Güldemann, 2008), i.e. a construction that contains sequences of two or more verbs without any syntactic marker of subordination. This would mean that pé is a verb. On the other hand, however, this item shows properties of a complementizer (Lawal, 1991). For instance, pé can occur in sentence initial position, which in Yorùbá is typically occupied by subordinating conjunctions. Also, unlike verbs, pé cannot undergo reduplication for nominalization (an ability that all Yorùbá verbs have). This seems to provide evidence for treating this item as a subordinate conjunction rather than a verb.

5.2.2 Adjective or Verb?

In some of our focus languages, the category of adjectives is not entirely distinct morpho-syntactically from verbs. In Wolof and Yorùbá, the notions that would be expressed by adjectives in English are encoded through verbs (McLaughlin, 2004). Igbo (Welmers, 2018) and Éwé (McLaughlin, 2004) have a very limited set of underived adjectives (8 and 5, respectively). For instance, in Wolof, unlike in English, an 'adjective' like *gaaw* 'be quick' does not need a copula (e.g. 'be' in English) to function as a predicate. Likewise, the Bambara item *téli* 'quick' as in the sentence So ka téli 'The horse is quick' (Aplonova and Tyers, 2017) has adjectival properties, as it is typically used to modify nouns and specify their properties or attributes. It also has verbal properties, as it can be used in the main predicative position functioning as a verb. This is signaled by the presence of the auxiliary ka, which is a special predicative marker ka that typically accompanies qualitative verbs (Vydrin, 2018).

5.2.3 Adverbs or particles?

The distinction between adverbs and particles was not always straightforward. For instance, many of our focus languages have ideophones, i.e. words that convey an idea by means of a sound (often reduplicated) that expresses an action, quality, manner, etc. Ideophones may behave like adverbs by modifying verbs for such categories as time, place, direction or manner. However, they can also function as verbal particles. For instance, in Wolof, an ideophone like *jërr* as in *tàng jërr* "very hot" (*tàng* means "to be hot") is an intensifier that only cooccurs as a particle of that verb. Thus, it would not be motivated to treat it as another POS other than PART. Whether such ideophones are PART or ADV or the like varies depending on the language.

6 Baseline Experiments

6.1 Baseline models

We provide POS tagging baselines using both CRF and multilingual PLMs. For the PLMs, we finetune three massively multilingual PLMs pre-trained on at least 100 languages (mBERT (Devlin et al., 2019), XLM-R (Conneau et al., 2020), and Rem-BERT (Chung et al., 2021)), and three Africacentric PLMs like AfriBERTa (Ogueji et al., 2021), AfroXLMR (Alabi et al., 2022), and AfroLM (Dossou et al., 2022) pre-trained on several African languages. The baseline models are:

CRF is one of the most successful sequence labeling approach prior to PLMs. CRF models the sequence labeling task as an undirected graphical model, using both labelled observations and contextual information as features. We implemented the CRF model using sklearn-crfsuite,⁶ using the following features: the word to be tagged, two consecutive previous and next words, the word in lowercase, prefixes and suffixes of words, length

⁶https://sklearn-crfsuite.readthedocs.io/

Model	bam	bbj	ewe	fon	hau	ibo	kin	lug	luo	mos	nya	pcm	sna	swa	tsn	twi	wol	xho	yor	zul	AVG
CRF	89.1	78.9	88.0	88.1	89.8	75.2	95.3	88.3	84.6	86.0	77.7	85.6	85.9	89.3	81.4	81.5	91.0	81.8	92.0	84.2	85.7
Massively-multilingual PL	Ms																				
mBERT (172M)	89.9	75.2	86.0	87.6	90.7	76.5	96.9	89.6	87.0	86.5	79.9	90.4	87.5	92.0	81.9	83.9	92.5	85.9	93.4	86.8	87.0
XLM-R-base (270M)	90.1	83.6	88.5	90.1	92.5	77.2	96.7	89.1	87.2	90.7	79.9	90.5	87.9	92.9	81.3	84.1	92.4	87.4	93.7	88.0	88.2
XLM-R-large (550M)	90.2	85.4	88.8	90.2	92.8	78.1	97.3	90.0	88.0	91.1	80.5	90.8	88.1	93.2	82.2	84.9	92.9	88.1	94.2	89.4	88.8
RemBERT (575M)	90.6	82.6	88.9	90.8	93.0	79.3	98.0	90.3	87.5	90.4	82.4	90.9	89.1	93.1	83.6	86.0	92.1	89.3	94.7	90.2	89.1
Africa-centric PLMs																					
AfroLM (270M)	89.2	77.8	87.5	82.4	92.7	77.8	97.4	90.8	86.8	89.6	81.1	89.5	88.7	92.8	83.8	83.9	92.1	87.5	91.1	88.8	87.6
AfriBERTa-large (126M)	89.4	79.6	87.4	88.4	93.0	79.3	97.8	89.8	86.5	89.9	79.7	89.8	87.8	93.0	82.5	83.7	91.7	86.1	94.5	86.9	87.8
AfroXLMR-base (270M)	90.2	83.5	88.5	90.1	93.0	79.1	98.2	90.9	86.9	90.9	82.7	90.8	89.2	92.9	82.7	84.3	92.4	88.5	94.5	89.4	88.9
AfroXLMR-large (550M)	90.5	85.3	88.7	90.4	93.0	78.9	98.4	91.6	88.1	91.2	83.2	91.2	89.5	93.2	83.0	84.9	92.9	88.7	95.0	90.1	89.4

Table 2: Accuracy of baseline models on MasakhaPOS dataset. We compare several multilingual PLMs including the ones trained on African languages. Average is over 5 runs.

	ADJ	ADP	ADV	AUX	CCONJ	DET	INTJ	NOUN	NUM	PART	PRON	PROPN	PUNCT	SCONJ	SYM	VERB	X	ACC
bam	41.0	77.0	72.0	82.0	91.0	0.0		91.0	90.0	95.0	97.0	82.0	100.0	71.0	25.0	83.0	0.0	90.7
bbj	71.0	80.0	67.0	89.0	84.0	85.0	0.0	82.0	86.0	78.0	91.0	92.0	100.0	88.0		86.0		85.6
ewe	72.0	83.0	57.0		94.0	89.0	100.0	91.0	91.0	87.0	90.0	93.0	100.0	84.0	13.0	82.0		88.7
fon	91.0	88.0	69.0	75.0	94.0	96.0		91.0	90.0	89.0	95.0	91.0	100.0	51.0		89.0		90.4
hau	86.0	80.0	71.0	96.0	89.0	84.0	0.0	94.0	98.0	95.0	76.0	98.0	99.0	86.0		96.0	62.0	92.9
ibo	95.0	89.0	56.0	98.0	76.0	79.0	0.0	70.0	95.0	0.0	98.0	95.0	100.0	6.0	0.0	81.0		79.2
kin	86.0	99.0	91.0	0.0	100.0	99.0		99.0	100.0	84.0	98.0	97.0	100.0	97.0	0.0	99.0	0.0	98.4
lug	71.0	96.0	72.0	90.0	90.0	76.0		94.0	93.0	94.0	15.0	94.0	100.0	89.0		92.0		91.6
luo	73.0	88.0	69.0	87.0	69.0	82.0		89.0	96.0	86.0	42.0	89.0	100.0	94.0	100.0	86.0	0.0	88.2
mos	64.0	83.0	72.0	91.0	93.0	84.0		91.0	93.0	94.0	83.0	90.0	100.0	95.0		92.0		91.2
nya	74.0	79.0	56.0	25.0	77.0	81.0	20.0	92.0	86.0	12.0	73.0	86.0	99.0	6.0		89.0		83.1
pcm	78.0	97.0	74.0	86.0	98.0	92.0		95.0	98.0	90.0	86.0	91.0	98.0	86.0	45.0	91.0		91.1
sna	51.0	94.0	44.0	87.0	89.0	83.0		95.0	96.0	0.0	78.0	92.0	99.0	58.0	60.0	94.0		89.4
swa	95.0	86.0	65.0	82.0	95.0	56.0		97.0	98.0	86.0	51.0	97.0	100.0	91.0		95.0	0.0	93.1
tsn	57.0	80.0	82.0	42.0	53.0	78.0	17.0	94.0	97.0	62.0	76.0	91.0	99.0	18.0	0.0	95.0	0.0	82.4
twi	55.0	82.0	68.0	52.0	87.0	93.0	0.0	86.0	77.0	21.0	82.0	92.0	100.0	9.0	0.0	87.0		84.8
wol	0.0	94.0	81.0	94.0	96.0	90.0	22.0	91.0	90.0	98.0	92.0	96.0	100.0	85.0	62.0	94.0		92.9
xho	73.0	69.0	47.0	17.0	88.0	54.0	0.0	87.0	100.0		80.0	95.0	100.0	57.0	0.0	90.0		88.3
yor	84.0	92.0	82.0	99.0	97.0	97.0		95.0	94.0	83.0	95.0	96.0	100.0	98.0		95.0	0.0	95.1
zul	68.0	26.0	72.0	21.0	67.0	82.0	0.0	91.0	99.0		81.0	99.0	100.0	91.0	100.0	91.0	96.0	90.0
AVE	69.2	83.1	68.4	69.1	86.4	79.0	15.9	90.8	93.4	69.7	79.0	92.8	99.7	68.0	33.8	90.4	19.8	89.4

Table 3: Tag distribution of the "AfroXLMR-large" -based POS tagger (reporting results from the first run). The tags with high average accuracy (> 90.0%) across all languages are highlighted in gray.

of the word, and other boolean features like is the word a digit, a punctuation mark, the beginning of a sentence or end of a sentence.

Massively multilingual PLM We fine-tune mBERT, XLM-R (base & large), and RemBERT pre-trained on 100-110 languages, but only few African languages. mBERT, XLM-R, and RemBERT were pre-trained on two (swa & yor), three (hau, swa, & xho), and eight (hau, ibo, nya, sna, swa, xho, yor, & zul) of our focus languages respectively. The three models were all pre-trained using masked language model (MLM), mBERT and RemBERT additionally use the next-sentence prediction objective.

Africa-centric PLMs We fine-tune AfriBERTa, AfroLM and AfroXLMR (base & large). The first two PLMs were pre-trained using XLM-R style pretraining, AfroLM additionally make use of active learning during pre-training to address data scarcity of many African languages. On the other hand, AfroXLMR was created through language adaptation (Pfeiffer et al., 2020) of XLM-R on 17 African languages, "eng", "fra", and "ara". AfroLM was pre-trained on all our focus languages, while AfriB- ERTa and AfroXLMR were pre-trained on 6 (hau, ibo, kin, pcm, swa, & yor) and 10 (hau, ibo, kin, nya, pcm, sna, swa, xho, yor, & zul) respectively. We fine-tune all PLMs using the Hug-gingFace Transformers library (Wolf et al., 2020).

For PLM fine-tuning, we make use of a maximum sequence length of 200, batch size of 16, gradient accumulation of 2, learning rate of 5e - 5, and number of epochs 50. The experiments were performed on using Nvidia V100 GPU.

6.2 Baseline results

Table 2 shows the results of training POS taggers for each focus language using the CRF and PLMs. Suprinsingly, the CRF model gave a very impressive result for all languages with only a few points below the best PLM (-3.7). In general, finetuning PLMs gave a better result for all languages. The mBERT performance is (+1.3) better in accuracy than CRF. AfroLM and AfriBERTa are only slightly better than mBERT with (< 1 point). One of the reasons for AfriBERTa's poor performance is that most of the languages are unseen during pre-training.⁷ On the other hand, AfroLM was pretrained on all our focus languages but on a small dataset (0.73GB) which makes it difficult to train a good representation for each of the languages covered during pre-training. Furthermore, XLM-R-base gave slightly better accuracy on average than both AfroLM (+0.6) and AfriBERTa (+0.4) despite seeing fewer African languages. However, the performance of the AfroXLMR-base exceeds that of XLM-R-base because it has been further adapted to 17 typologically diverse African languages, and the performance (\pm 0.1) is similar to the larger PLMs i.e RemBERT and XLM-R-large.

Impressive performance was achieved by large versions of massively multilingual PLMs like XLM-R-large and RemBERT, and AfroXLMR (base & large) i.e better than mBERT (+1.8 to +2.4) and better than CRF (+3.1 to +3.7). The performance of the large PLMs (e.g. AfroXLMRlarge) is larger for some languages when compared to mBERT like bbj (+10.1), mos (+4.7), nya (+3.3), and zul (+3.3). Overall, AfroXLMRlarge achieves the best accuracy on average over all languages (89.4) because it has been pre-trained on more African languages with larger monolingual data and it's large size. Interestingly, 11 out of 20 languages reach an impressive accuracy of (> 90%) with the best PLM which is an indication of consistent and high quality POS annotation.

Accuracy by tag distribution Table 3 shows the POS tagging results by tag distribution using our best model "AfroXLMR-large". The tags that are easiest (with accuracy over > 90%) to detect across all languages are PUNCT, NUM, PROPN, NOUN, and VERB, while the most difficult are SYM, INTJ, and X tags. The difficult tags are often infrequent, which does not affect the overall accuracy. Surprisingly, a few languages like Yorùbá and Kinyarwanda, have very good accuracy on almost all tags except for the infrequent tags in the language.

7 Cross-lingual Transfer

7.1 Experimental setup for effective transfer

The effectiveness of zero-shot cross-lingual transfer depends on several factors including the choice of the best performing PLM, choice of an effective cross-lingual transfer method, and the choice of the best source language for transfer. Oftentimes, the source language chosen for cross-lingual transfer is English due to the availability of training data which may not be ideal for distant languages especially for POS tagging (de Vries et al., 2022). To further improve performance, parameter-efficient fine-tuning approaches (Pfeiffer et al., 2020; Ansell et al., 2022) can be leveraged with additional monolingual data for both source and target languages. We highlight how we combine these different factors for effective transfer below:

Choice of source languages Prior work on the choice of source language for POS tagging shows that the most important features are geographical similarity, genetic similarity (or closeness in language family tree) and word overlap between source and target language (Lin et al., 2019). We choose seven source languages for zero-shot transfer based on the following criteria (1) availability of POS training data in UD,⁸. Only three African languages satisfies this criteria (Wolof, Nigerian-Pidgin, and Afrikaans) (2) geographical proximity to African languages - this includes nonindigeneous languages that have official status in Africa like English, French, Afrikaans, and Arabic. (3) language family similarity to target languages. The languages chosen are: Afrikaans (afr), Arabic (ara), English (eng), French (fra), Nigerian-Pidgin (pcm), Wolof (wol), and Romanian (ron). While Romanian does not satisfy the last two criteria - it was selected based on the findings of de Vries et al. (2022) - Romanian achieves the best transfer performance to the most number of languages in UD. Appendix C shows the data split for the source languages.

Parameter-efficient cross-lingual transfer The standard way of zero-shot cross-lingual transfer involves fine-tuning a multilingual PLM on the source language labelled data (e.g. on a POS task), and evaluate it on a target language. We refer to it as FT-Eval (or Fine-tune & evaluate). However, the performance is often poor for unseen languages in PLM and distant languages. One way to address this is to perform language adaptation using monolingual corpus in the target language before fine-tuning on the downstream task (Pfeiffer et al., 2020), but this setup does not scale to many languages since it requires modifying all the parameters of the PLM and requires large disk space (Alabi et al., 2022). Several parameter-efficient approaches have been proposed

⁷14 out of 20 languages are unseen

⁸https://universaldependencies.org/



Figure 1: Zero-shot cross-lingual transfer results using FT-Eval, LT-SFT and MAD-X. Average over 20 languages. Experiments performed using AfroXLMR-base. Evaluation metric is Accuracy.

like Adapters (Houlsby et al., 2019) and Lottery-Ticketing Sparse Fine-tunings (LT-SFT) (Ansell et al., 2022) ----they are also modular and compos-able making them ideal for cross-lingual transfer.

Here, we make use of MAD-X 2.0⁹ adapter based approach (Pfeiffer et al., 2020, 2021) and LT-SFT approach. The setup is as follows: (1) We train language adapters/SFTs using monolingual news corpora of our focus languages. We perform language adaptation on the news corpus to match the POS task domain, similar to (Alabi et al., 2022). We provide details of the monolingual corpus in Appendix E. (2) We train a task adapter/SFT on the source language labelled data using source language adapter/SFT. (3) We substitute the source language adapter/SFT with the target language/SFT to run prediction on the target language test set, while retaining the task adapter.

Choice of PLM We make use of AfroXLMRbase as the backbone PLM for all experiments because it gave an impressive performance in Table 2, and the availability of language adapters/SFTs for some of the languages by prior works (Pfeiffer et al., 2021; Ansell et al., 2022; Alabi et al., 2022). When a target language adapter/SFT of AfroXLMR-base is absent, XLM-R-base language adapter/SFT can be used instead since they share the same architecture and number of parameters, as demonstrated in Alabi et al. (2022). We did not find XLM-R-large based adapters and SFTs online,¹⁰ and they are time-consuming to train especially for high-resource languages like English.

Experimental Results 7.2

Parameter-efficient fine-tuning are more effective Figure 1 shows the result of cross-lingual

¹⁰https://adapterhub.ml/

transfer from seven source languages with POS training data in UD, and their average accuracy on 20 African languages. We report the performance of the standard zero-shot cross-lingual transfer with AfroXLMR-base (i.e. FT-Eval), and parameterefficient fine-tuning approaches i.e MAD-X and LT-SFT. Our result shows that MAD-X and LT-SFT gives significantly better results than FT-Eval, the performance difference is over 10% accuracy on all languages. This shows the effectiveness of parameter-efficient fine-tuning approaches on cross-lingual transfer for low-resource languages despite only using small monolingual data (433KB - 50.2MB, as shown in Appendix E) for training target language adapters and SFTs. Furthermore, we find MAD-X to be slightly better than LT-SFT especially when ron (+3.5), fra (+3.2), pcm (+2.9), and eng (+2.6) are used as source languages.

The best source language In general, we find eng, ron, and wol to be better as source languages to the 20 African languages. For the FT-Eval, eng and ron have similar performance. However, for LT-SFT, wol was slightly better than the other two, probably because we are transfering from an African language that shares the same family or geographical location to the target languages. For MAD-X, eng was surprisingly the best choice.

Multi-source fine-tuning leads to further gains Table 4 shows that co-training the best three source languages (eng, ron, and wol) leads to improved performance, reaching an impressive accuracy of 68.8% with MAD-X. For the FT-Eval, we performed multi-task training on the combined training set of the three languages. LT-SFT supports multi-source fine-tuning --- where a task SFT can be trained on data from several languages jointly. However, MAD-X implementation does not support multi-source fine-tuning. We created our ver-

⁹an extension of MAD-X where the last adapter layers are dropped, which has been shown to improve performance

Method	bam	bbj	ewe	fon	hau	ibo	kin	lug	luo	mos	nya	pcm	sna	swa	tsn	twi	wol	xho	yor	zul	AVG	AVG*
eng as a source																						
FT-Eval	52.1	31.9	47.8	32.5	67.1	74.5	63.9	57.8	38.4	45.3	59.0	82.1	63.7	56.9	49.4	35.9	35.9	45.9	63.3	48.8	52.6	51.9
LT-SFT	67.9	57.6	67.9	55.5	69.0	76.3	64.2	61.0	74.5	70.3	59.4	82.4	64.6	56.9	49.5	52.1	78.2	45.9	65.3	49.8	63.4	61.5
MAD-X	62.9	58.5	68.7	55.8	67.0	77.8	70.9	65.7	73.0	71.8	70.1	83.2	69.8	61.2	49.8	53.0	75.2	57.1	66.9	60.9	66.0	64.5
ron as a source	languag	e																				
FT-Eval	46.5	30.5	37.6	30.9	67.3	77.7	73.3	56.9	36.7	40.6	62.2	78.9	66.3	61.0	55.8	35.7	33.8	49.6	63.5	56.3	53.1	52.7
LT-SFT	60.6	57.0	64.9	60.4	67.5	77.4	68.2	58.5	70.2	67.9	58.2	78.1	64.6	59.7	57.4	55.7	81.9	46.3	64.8	51.2	63.5	61.7
MAD-X	63.5	62.2	66.6	61.8	66.5	80.0	73.5	62.7	76.5	71.8	66.0	83.7	71.1	64.5	61.2	53.5	79.5	48.6	69.5	57.8	67.0	65.4
wol as a source	languag	e																				
FT-Eval	40.8	36.5	39.8	37.4	55.1	58.6	49.2	51.8	35.1	44.9	49.0	51.6	53.8	42.9	45.0	38.4	88.6	46.0	52.5	45.5	48.1	45.7
LT-SFT (N)	64.4	64.3	69.8	63.0	67.0	79.7	63.7	64.0	74.1	72.2	56.5	72.7	67.7	53.0	51.3	56.2	92.5	46.0	69.8	47.7	64.8	62.8
MAD-X (N)	46.6	41.8	47.2	37.8	53.9	51.8	41.0	39.0	46.5	44.0	38.3	40.2	44.3	38.8	44.6	40.1	85.6	39.2	46.4	36.0	45.2	43.2
MAD-X (N+W)	61.7	63.6	68.9	63.1	66.8	77.0	67.8	69.1	73.7	71.3	63.2	75.1	68.9	55.8	50.7	54.9	90.4	49.6	70.0	51.7	65.7	63.8
multi-source	: en	g-ron-	-wol																			
FT-Eval	44.2	36.3	39.3	39.3	69.4	78.5	70.6	59.2	35.5	46.8	60.9	81.4	65.8	58.5	53.8	38.8	89.1	48.8	65.2	53.5	56.7	53.6
LT-SFT	67.4	64.6	70.0	64.2	70.4	81.1	68.7	63.9	76.4	73.9	58.8	83.0	69.6	57.3	52.7	57.2	93.1	45.8	69.8	48.3	66.8	64.4
MAD-X	66.2	65.5	70.3	64.9	69.1	82.3	73.1	68.0	75.1	74.2	69.2	83.9	69.4	62.6	53.6	55.2	90.1	52.3	70.8	59.4	68.8	66.7

Table 4: Cross-lingual transfer to MasakhaPOS. Zero-shot Evaluation using FT-Eval, LT-SFT, and MAD-X, with ron, eng, and wol as source languages. Experiments are based on AfroXLMR-base. Non-Bantu Niger-Congo languages highlighted with gray. AVG* excludes pcm and wol from the average since they are source languages.

sion of multi-source fine-tuning following these steps: (1) We combine all the training data of the three languages (2) We train a task adapter using the combined data and one of the best source languages' adapter. We experiment using eng, ron, and wol as source language adapter for the combined data. Our experiment shows that eng or wol achieves similar performance when used as language adapter for multi-source fine-tuning. We only added the result using wol as source adapter on Table 4. Appendix Appendix F provides more details on MAD-X multi-source fine-tuning.

Performance difference by language family Table 4 shows the transfer result per language for the three best source languages. wol has a better transfer performance to non-Bantu Niger-Congo languages in West Africa than eng and ron, especially for bbj, ewe, fon, ibo, mos, twi, and yor despite having a smaller POS training data (1.2k sentences) compared to ron (8k sentences) and eng (12.5k sentences). Also, wol adapter was trained on a small monolingual corpus (5.2MB). This result aligns with prior studies that choosing a source language from the same family leads to more effective transfer (Lin et al., 2019; de Vries et al., 2022). However, we find MAD-X to be more sensitive to the size of monolingual corpus. We obtained a very terrible transfer accuracy when we only train language adapter for wol on the news domain (2.5MB) i.e MAD-X (N), lower than FT-Eval. By additionally combining the news corpus with Wikipedia corpus (2.7MB) i.e MAD-X (N+W), we were able to obtain an impressive result comparable to LT-SFT. This highlight the importance of using larger monolingual corpus to train source language adapter. wol was not the best source language for

Bantu languages probably because of the difference in language characteristics. For example, Bantu languages are very morphologically-rich while non-Bantu Niger-Congo languages (like wol) are not. Our further analysis shows that sna was better in transferring to Bantu languages. Appendix G provides result for the other source languages.

8 Conclusion

In this paper, we created MasakhaPOS, the largest POS dataset for 20 typologically-diverse African languages. We showed that POS annotation of these languages based on the UD scheme can be quite challenging, especially with regard to word segmentation and POS ambiguities. We provide POS baseline models using CRF and by fine-tuning multilingual PLMs. We analyze cross-lingual transfer on MasakhaPOS dataset in single-source and multi-source settings. An important finding that emerged from this study is that choosing the appropriate transfer languages substantially improves POS tagging for unseen languages. The transfer performance is particularly effective when pretraining includes a language that shares typological features with the target languages.

9 Limitations

Some Language families in Africa not covered For example, Khoisan and Austronesian (like Malagasy). We performed extensive analysis and experiments on Niger-Congo languages but we only covered one language each in the Afro-asiatic (Hausa) and Nilo-Saharan (Dholuo) families.

News domain Our annotated dataset belong to the news domain, which is a popular domain in UD. However, the POS dataset and models may not

generalize to other domains like speech transcript, conversation data etc.

Transfer results may not generalize to all NLP tasks We have only experimented with POS task, the best transfer language e.g for non-Bantu Niger-Congo languages i.e Wolof, may not be the same for other NLP tasks.

10 Ethics Statement or Broader Impact

Our work aims to understand linguistic characteristics of African languages, we do not see any potential harms when using our POS datasets and models to train ML models, the annotated dataset is based on the news domain, and the articles are publicly available, and we believe the dataset and POS annotation is unlikely to cause unintended harm.

Also, we do not see any privacy risks in using our dataset and models because it is based on news domain.

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A Language Characteristics

Table 5 provides the details about the language characteristics.

B Annotation Agreement

Table 6 provides POS annotation agreements at the sentence level for 13 out of the 20 focus languages.

Language	No. of Letters	Latin Letters Omitted	Letters added	Tonality	diacritics	Word Order	Morphological typology	Inflectional Morphology (WALS)	Noun Classes
Bambara (bam)	27	q,v,x	ε, ο, μ, η	yes, 2 tones	yes	SVO & SOV	isolating	strong suffixing	absent
Ghomálá' (bbj)	40	q, w, x, y	bv, dz, θ, aθ, ε, gh, ny, nt, ŋ, ŋk, ɔ, pf, mpf, sh, ts, ʉ, zh, '	yes, 5 tones	yes	SVO	agglutinative	strong prefixing	active, 6
Éwé (ewe)	35	c, j, q	d, dz, ε, f, gb, χ, kp, ny, η, ο, ts, υ	yes, 3 tones	yes	SVO	isolating	equal prefixing and suffixing	vestigial
Fon (fon)	33	q	d, ɛ,gb, hw, kp, ny, ɔ, xw	yes, 3 tones	yes	SVO	isolating	little affixation	vestigial
Hausa (hau)	44	p,q,v,x	6, d, k, y, kw, kw, gw, ky, ky, gy, sh, ts	yes, 2 tones	no	SVO	agglutinative	little affixation	absent
Igbo (ibo)	34	c, q, x	ch, gb, gh, gw, kp, kw, nw, ny, o, o, sh, u	yes, 2 tones	yes	SVO	agglutinative	little affixation	vestigial
Kinyarwanda (kin)	30	q, x	cy, jy, nk, nt, ny, sh	yes, 2 tones	no	SVO	agglutinative	strong prefixing	active, 16
Luganda (lug)	25	h, q, x	ŋ, ny	yes, 3 tones	no	SVO	agglutinative	strong prefixing	active, 20
Luo (luo)	31	c, q, x, v, z	ch, dh, mb, nd, ng', ng, ny, nj, th, sh	yes, 4 tones	no	SVO	agglutinative	equal prefixing and suffixing	absent
Mossi (mos)	26	c, j, q, x	', ε, ι, υ	yes, 2 tones	yes	SVO	isolating	strongly suffixing	active, 11
Chichewa (nya)	31	q, x, y	ch, kh, ng, ŋ, ph, tch, th, ŵ	yes, 2 tones	no	SVO	agglutinative	strong prefixing	active, 17
Naija (pcm)	26	-	-	no	no	SVO	mostly analytic	strongly suffixing	absent
chiShona (sna)	29	c, l, q, x	bh, ch, dh, nh, sh, vh, zh	yes, 2 tones	no	SVO	agglutinative	strong prefixing	active, 20
Swahili (swa)	33	x, q	ch, dh, gh, kh, ng', ny, sh, th, ts	no	yes	SVO	agglutinative	strong suffixing	active, 18
Setswana (tsn)	36	c, q, v, x, z	ê, kg, kh, ng, ny, ô, ph, š, th, tl, tlh, ts, tsh, tš, tšh	yes, 2 tones	no	SVO	agglutinative	strong prefixing	active, 18
Akan/Twi (twi)	22	c,j,q,v,x,z	8, 0	yes, 5 tones	no	SVO	isolating	strong prefixing	active, 6
Wolof (wol)	29	h,v,z	ŋ, à, é, ë, ó, ñ	no	yes	SVO	agglutinative	strong suffixing	active, 10
isiXhosa (xho)	68	-	bh, ch, dl, dy, dz, gc, gq, gr, gx, hh, hl, kh, kr, lh, mh, ng, ngc, ngh, ngq, ngx, nkq, nkx, nh, nkc, nx, ny, nyh, ph, qh, rh, sh, th, ths, thsh, ts, tsh, ty, tyh, wh, xh, vh, zh	yes, 2 tones	no	SVO	agglutinative	strong prefixing	active, 17
Yorùbá (yor)	25	c, q, v, x, z	e, gb, ș , o	yes, 3 tones	yes	SVO	isolating	little affixation	vestigial, 2
isiZulu (zul)	55	_	nx, ts, nq, ph, hh, ny, gq, hl, bh, nj, ch, ngc, ngq, th, ngx, kl, ntsh, sh, kh, tsh, ng nk gy xh gc mb dl nc ab	yes, 3 tones	no	SVO	agglutinative	strong prefixing	active, 17

Table 5: Linguistic Characteristics of the Languages

Lang.	No. agreed annotation	agreed annotation (%)	Lang.	No. agreed annotation	agreed annotation (%)
bam	1,091	77.9	pcm	1,073	76.6
ewe	616	44.0	tsn	1,058	24.4
hau	1,079	77.1	twi	1,306	93.2
kin	1,127	80.5	xho	1,378	98.4
lug	937	66.9	yor	1,059	75.6
luo	564	40.3	zul	905	64.6
mos	829	49.2			

Table 6: Number of sentences with agreed annotations and their percentages

Language	Data Source	# Train/# dev/ # test
Afrikaans(afr)	UD_Afrikaans-AfriBooms	1,315/ 194/ 425
Arabic (ara)	UD_Arabic-PADT	6,075/ 909/ 680
English (eng)	UD_English-EWT	12,544/ 2001/ 2077
French (fra)	UD_French-GSD	14,450/ 1,476/ 416
Naija (pcm)	UD_Naija-NSC	7,279/ 991/ 972
Romanian (ron)	UD_Romanian-RRT	8,043/752/729
Wolof (wol)	UD_Wolof-WTB	1,188/ 449/ 470

Table 7: Data Splits for UD POS datasets used assource languages for cross-lingual transfer.

C UD POS data split

Table 7 provides the UD POS corpus found online that we make use for determining the best transfer languages

D Hyper-parameters for Experiments

Hyper-parameters for Baseline Models The PLMs were trained for 20 epochs with a learning rate of 5e-5 using huggingface transformers (Wolf et al., 2020). We make use of a batch size of 16

Hyper-parameters for adapters We train the task adapter using the following hyper-parameters: batch size of 8, 20 epochs, "pfeiffer" adapter config, adapter reduction factor of 4 (except for Wolof,

where we make use of adapter reduction factor of 1), and learning rate of 5e-5. For the language adapters, we make use of 100 epochs or maximum steps of 100K, minimum number of steps is 30K, batch size of 8, "pfeiffer+inv" adapter config, adapter reduction factor of 2, learning rate of 5e-5, and maximum sequence length of 256.

Hyper-parameters for LT-SFT We make use of the default setting used by the Ansell et al. (2022) paper.

E Monolingual data for Adapter/SFTs language adaptation

Table 8 provides the UD POS corpus found online that we make use for determining the best transfer languages

F MAD-X multi-source fine-tuning

Figure 2 provides the result of MAD-X with different source languages, and multi-source finetuning using either eng, ron or wol as language adapter for task adaptation prior to zero-shot transfer. Our result shows that making of wol as lan-

Language	Source	Size (MB)
Bambara (bam)	MAFAND-MT (Adelani et al., 2022a)	0.8MB
Ghomálá' (bbj)	MAFAND-MT (Adelani et al., 2022a)	0.4MB
Éwé (ewe)	MAFAND-MT (Adelani et al., 2022a)	0.5MB
Fon (fon)	MAFAND-MT (Adelani et al., 2022a)	1.0MB
Hausa (hau)	VOA (Palen-Michel et al., 2022)	46.1MB
Igbo (ibo)	BBC Igbo (Ogueji et al., 2021)	16.6MB
Kinyarwanda (kin)	KINNEWS (Niyongabo et al., 2020)	35.8MB
Luganda (lug)	Bukedde (Alabi et al., 2022)	7.9MB
Luo (luo)	Ramogi FM news (Adelani et al., 2021) and MAFAND-MT (Adelani et al., 2022a)	1.4MB
Mossi (mos)	MAFAND-MT (Adelani et al., 2022a)	0.7MB
Naija (pcm)	BBC (Alabi et al., 2022)	50.2MB
Chichewa (nya)	Nation Online Malawi (Siminyu et al., 2021)	4.5MB
chiShona (sna)	VOA (Palen-Michel et al., 2022)	28.5MB
Kiswahili (swa)	VOA (Palen-Michel et al., 2022)	17.1MB
Setswana (tsn)	Daily News (Adelani et al., 2021), MAFAND-MT (Adelani et al., 2022a)	1.9MB
Twi (twi)	MAFAND-MT (Adelani et al., 2022a)	0.8KB
Wolof (wol)	Lu Defu Waxu, Saabal, Wolof Online, and MAFAND-MT (Adelani et al., 2022a)	2.3MB
isiXhosa (xho)	Isolezwe Newspaper	17.3MB
Yorùbá (yor)	BBC Yorùbá (Alabi et al., 2022)	15.0MB
isiZulu (zul)	Isolezwe Newspaper	34.3MB
Romanian (ron)	Wikipedia	500MB
French (fra)	Wikipedia (a subset)	500MB

Table 8: Monolingual News Corpora used for language adapter and SFT training, and their sources and size (MB)



Figure 2: MAD-X: Cross-lingual Experiments on MasakhaPOS. Zero-shot Evaluation using afr, ara, eng, fra, ron, pcm and wol as source languages. Experiments based on AfroXLMR-base. ave* excludes pcm and wol from the average since they are also source languages.

guage adapters leads to slightly better accuracy (69.1%) over eng (68.7%) and ron (67.8%). But in general, either one can be used, and they all give an impressive performance over LT-SFT, as shown in Table 9.

G Cross-lingual transfer from all source languages

Table 9 shows the result of cross-lingual transfer from each source language (afr, ara, eng, fra, pcm, ron, and wol) to each of the African languages. We extended the evaluation to include sna (since it was recommended as the best transfer language for a related task – named entity recognition by (Adelani et al., 2022b)) by using the newly created POS corpus. We also tried other Bantu languages like kin and swa, but their performance was worse than sna. Our evaluation shows that sna results in better transfer to Bantu languages because of it's rich morphology. We achieved the best result for all languages using multi-source transfer from (eng, ron, wol, sna) languages.

Method	bam	bbj	ewe	fon	hau	ibo	kin	lug	luo	mos	nya	pcm	sna	swa	tsn	twi	wol	xho	yor	zul	AVG	AVG*
ara as a source	languag	e																				
FT-Eval	26.4	10.0	16.0	14.2	47.7	62.5	57.1	35.4	15.3	17.0	53.7	66.4	56.0	58.4	42.9	14.1	13.5	39.0	46.9	44.8	36.9	37.1
LT-SFT	41.0	30.7	41.2	45.0	47.3	62.9	54.0	48.7	56.2	43.2	54.4	63.3	53.6	59.4	44.8	39.9	51.0	36.8	50.6	44.8	48.4	48.0
MAD-X	44.5	36.5	50.9	45.9	48.5	59.5	55.5	51.1	60.5	46.7	53.4	66.8	53.8	59.1	40.4	37.9	52.3	40.3	52.3	44.6	50.0	49.7
pcm as a source	languag	e																				
FT-Eval	16.0	8.6	14.3	4.9	58.0	64.9	48.9	35.9	13.0	11.0	47.5	74.6	51.9	50.9	32.8	5.3	7.3	25.9	46.9	30.9	32.8	33.2
LT-SFT	44.4	39.4	51.1	38.1	59.2	66.6	47.9	53.5	61.3	52.3	49.3	75.3	48.9	50.6	40.8	35.3	63.9	25.1	58.3	30.6	49.6	48.8
MAD-X	42.1	43.6	53.5	39.4	57.3	68.2	55.7	58.1	60.1	51.9	59.6	75.8	57.5	55.7	44.8	36.9	58.9	32.9	57.1	40.6	52.5	51.8
afr as a source	languag	e																				
FT-Eval	54.8	25.4	38.3	31.3	61.4	73.6	67.1	48.6	29.4	35.2	56.1	77.3	56.0	57.5	49.0	32.9	32.5	43.8	63.8	44.3	48.9	49.4
LT-SFT	69.2	55.6	64.0	52.5	62.8	74.7	66.1	59.0	69.4	63.4	54.4	79.7	58.4	57.1	48.5	49.0	79.3	41.0	64.3	41.5	60.5	59.6
MAD-X	61.9	56.1	63.9	53.0	63.0	75.2	68.2	60.2	68.1	63.4	62.0	80.8	61.1	60.6	50.4	48.6	75.7	43.8	65.2	46.0	61.4	60.6
fra as a source	languag	e																				
FT-Eval	41.0	15.2	27.5	16.1	64.1	73.0	67.7	53.4	21.9	21.3	65.2	77.9	64.4	62.2	51.8	16.8	17.7	45.8	61.6	46.5	45.6	46.1
LT-SFT	60.6	52.2	63.3	60.2	63.9	75.6	63.4	57.6	69.0	65.2	66.4	79.7	63.0	61.2	52.4	48.6	78.3	43.9	64.7	44.3	61.7	60.7
MAD-X	62.0	57.9	64.2	59.4	66.9	78.7	71.3	64.1	74.0	67.7	70.2	83.4	68.6	65.4	53.0	48.1	78.3	46.0	67.8	50.2	64.9	63.9
eng as a source	anguag	e																				
FT-Eval	52.1	31.9	47.8	32.5	67.1	74.5	63.9	57.8	38.4	45.3	59.0	82.1	63.7	56.9	52.6	35.9	35.9	45.9	63.3	48.8	52.6	52.9
LT-SFT	67.9	57.6	67.9	55.5	69.0	76.3	64.2	61.0	74.5	70.3	59.4	82.4	64.6	56.9	49.5	52.1	78.2	45.9	65.3	49.8	63.4	62.5
MAD-X	62.9	58.5	68.7	55.8	67.0	77.8	70.9	65.7	73.0	71.8	70.1	83.2	69.8	61.2	49.8	53.0	75.2	57.1	66.9	60.9	66.0	65.2
ron as a source	anguag	e																				
FT-Eval	46.5	30.5	37.6	30.9	67.3	77.7	73.3	56.9	36.7	40.6	62.2	78.9	66.3	61.0	55.8	35.7	33.8	49.6	63.5	56.3	53.1	53.4
LT-SFT	60.6	57.0	64.9	60.4	67.5	77.4	68.2	58.5	70.2	67.9	58.2	78.1	64.6	59.7	57.4	55.7	81.9	46.3	64.8	51.2	63.5	62.4
MAD-X	63.5	62.2	66.6	61.8	66.5	80.0	73.5	62.7	76.5	71.8	66.0	83.7	71.1	64.5	61.2	53.5	79.5	48.6	69.5	57.8	67.0	66.1
wol as a source	anonao	e																				
FT-Eval	40.8	36.5	39.8	37.4	55.1	58.6	49.2	51.8	35.1	44.9	49.0	51.6	53.8	42.9	45.0	38.4	88.6	46.0	52.5	45.5	48.1	45.6
LT-SFT (N)	64.4	64.3	69.8	63.0	67.0	79.7	63.7	64.0	74.1	72.2	56.5	72.7	67.7	53.0	51.3	56.2	92.5	46.0	69.8	47.7	64.8	63.1
MAD-X (N)	46.6	41.8	47.2	37.8	53.9	51.8	41.0	39.0	46.5	44.0	38.3	40.2	44.3	38.8	44.6	40.1	85.6	39.2	46.4	45.2	43.0	43.3
MAD-X (N+W)	61.7	63.6	68.9	63.1	66.8	77.0	67.8	69.1	73.7	71.3	63.2	75.1	68.9	55.8	50.7	54.9	90.4	49.6	70.0	51.7	65.7	64.1
ena as a source	anouao	e																				
FT-Eval	42.6	26.2	41.7	29.5	60.5	68.2	73.7	75.0	42.2	34.9	69.3	65.7	89.2	63.4	48.9	33.3	35.8	59.5	59.2	67.9	54.3	53.4
LT-SFT	52.2	57.5	66.0	55.4	60.5	71.9	69.0	80.1	75.7	58.1	70.4	60.2	89.9	63.5	50.6	65.8	71.6	62.7	62.2	72.9	65.8	64.2
MAD-X	50.3	57.0	65.3	56.3	64.1	71.9	75.0	79.2	75.9	59.8	70.6	68.6	89.7	63.2	52.7	61.0	75.3	61.8	57.8	69.8	66.3	64.5
multi-source	· en	-ron	-wol																			
FT-Eval	44.2	36.3	39.3	39.3	69.4	78.5	70.6	59.2	35.5	46.8	60.9	814	65.8	58.5	53.8	38.8	89.1	48.8	65.2	53.5	567	54.4
LT-SFT	67.4	64.6	70.0	64.2	70.4	81.1	68.7	63.9	76.4	73.9	58.8	83.0	69.6	57.3	52.7	57.2	93.1	45.8	69.8	48.3	66.8	65.2
MAD-X	66.2	65.5	70.3	64.9	69.1	82.3	73.1	68.0	75.1	74.2	69.2	83.9	69.4	62.6	53.6	55.2	90.1	52.3	70.8	59.4	68.8	67.5
ET Eval	. en	35.0	30.6	41.0	69.5	787	76.0	717	37.4	46.8	71.0	824	88.0	63.8	517	38.8	80.2	50.6	65.6	67.3	61.1	58.0
IT SET	-5.1	64.7	68.5	65.1	71.0	81.2	75.3	80.2	70 2	73.5	73.6	83.6	80.1	64.3	51.7	60.0	03.2	61.8	60.1	70.2	72 1	70.0
MAD-X	59.0	64.7	70.9	64.3	69.8	82.5	76.9	80.2	78.8	70.1	74.2	85.0	89.1	65.7	55.0	60.7	86.5	60.7	71.0	69.6	71.8	70.0
mad-A	59.0	04.5	70.9	04.5	02.0	02.5	70.9	00.7	70.0	70.1	/ 4.4	05.1	09.1	05.7	55.0	00.7	00.5	00.7	/1.0	09.0	/1.0	/0.0

Table 9: **Cross-lingual transfer to MasakhaPOS**. Zero-shot Evaluation using FT-Eval, LT-SFT, and MAD-X, with ron, eng, wol and sna as source languages. Experiments are based on AfroXLMR-base. Non-Bantu Niger-Congo languages highlighted with gray (except for Bambara that is often disputed as a different language family — Mande) while those of Bantu Niger-Congo languages are highlighted with cyan . AVG* excludes sna and wol from the average since they are source languages.

ACL 2023 Responsible NLP Checklist

A For every submission:

- A1. Did you describe the limitations of your work? *section 9*
- A2. Did you discuss any potential risks of your work? *section 10*
- A3. Do the abstract and introduction summarize the paper's main claims? *Section 1 (for the introduction) and no section number for the abstract*
- A4. Have you used AI writing assistants when working on this paper? *Left blank.*

B ☑ Did you use or create scientific artifacts?

Sections 4 and 6

- B1. Did you cite the creators of artifacts you used? Sections 4 and 6
- B2. Did you discuss the license or terms for use and / or distribution of any artifacts? Section 4
- ☑ B3. Did you discuss if your use of existing artifact(s) was consistent with their intended use, provided that it was specified? For the artifacts you create, do you specify intended use and whether that is compatible with the original access conditions (in particular, derivatives of data accessed for research purposes should not be used outside of research contexts)? Section 1
- □ B4. Did you discuss the steps taken to check whether the data that was collected / used contains any information that names or uniquely identifies individual people or offensive content, and the steps taken to protect / anonymize it? *Not applicable. Left blank.*
- B5. Did you provide documentation of the artifacts, e.g., coverage of domains, languages, and linguistic phenomena, demographic groups represented, etc.? Section 3, 5 and 9
- B6. Did you report relevant statistics like the number of examples, details of train / test / dev splits, etc. for the data that you used / created? Even for commonly-used benchmark datasets, include the number of examples in train / validation / test splits, as these provide necessary context for a reader to understand experimental results. For example, small differences in accuracy on large test sets may be significant, while on small test sets they may not be.

We provided number of tokens, sentences and the data split into train/test/dev.

C ☑ Did you run computational experiments?

Sections 6 and 7

C1. Did you report the number of parameters in the models used, the total computational budget (e.g., GPU hours), and computing infrastructure used? Section 6

The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.

- ✓ C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
 Appendix D
- C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run? *Section* 7
- C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)? Left blank.

D D id you use human annotators (e.g., crowdworkers) or research with human participants? Section 4

- ✓ D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.? Section 4
- ✓ D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants' demographic (e.g., country of residence)?
 Section 4
- D3. Did you discuss whether and how consent was obtained from people whose data you're using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
 Not applicable. The dataset used is already publicly available.
- □ D4. Was the data collection protocol approved (or determined exempt) by an ethics review board? *Not applicable. Left blank.*
- ✓ D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data? Section 3